Science & Technology Development Journal – Economics - Law and Management 2024, ():1-10

Open Access Full Text Article

Research Article

Personalized learning paths recommendation system with collaborative filtering and content-based approaches

Tran Duong Thanh Phong[1,2], Vu Bao Khang[1,2], Doan Nhat Minh[1,2], Dang Truc Quynh[1,2], Dang Viet Quang[1,2], Ho Trung Thanh[1,2,*]

Use your smartphone to scan this QR code and download this article

[1]*University of Economics and Law, Ho Chi Minh City, Vietnam*

[2]*Vietnam National University, Ho Chi Minh City, Vietnam*

Correspondence

Ho Trung Thanh, University of Economics and Law, Ho Chi Minh City, Vietnam

Vietnam National University, Ho Chi Minh City, Vietnam

Email: thanhht@uel.edu.vn

History

- Received: 19-02-2024
- Accepted: 27-5-2024
- Published Online:

DOI :

Check for updates

ABSTRACT

Recommender systems have undergone a transformative evolution, reshaping user interactions across diverse domains. Notably, the emphasis on personalized learning paths has grown significantly in education. This research paper delves into the performance evaluation of User-based Collaborative Filtering and Content-based recommendation techniques to develop innovative recommender systems explicitly tailored to Information Systems students. By integrating the primary dataset collection rooted within the Knowledge - Skill - Attitude framework for students in the Faculty of Information Systems at the University of Economics and Law, this study assesses how effectively these two separate models develop personalized recommendation systems. Furthermore, the empirical evaluation of two distinct models, the Collaborative Filtering and Content-Based approach, across key metrics such as Precision, Recall, and F1-Score, provides a comprehensive view of their effectiveness in generating a Recommendation System for the University of Economics and Law. Findings reveal that the Collaborative Filtering approach excels in recision, achieving a perfect score. At the same time, the Content-based technique demonstrates superior recall capabilities, suggesting its potential to cater to diverse educational needs. This paper also highlights the transformative role of recommendation systems in higher education, particularly in enhancing student engagement through personalized learning experiences and aligning curricula with industry requirements. Recognizing the limitations inherent in deploying either model independently, future research should propose a hybrid approach that combines the strengths of both Collaborative Filtering and Content-based methods, aiming to mitigate the existing drawbacks of the distinct model. The findings provide actionable insights for students, universities, and businesses to enhance educational content and career development tools and pave the way for future research on hybrid recommendation methodologies, which promise a more tailored and efficient learning experience for learners.

Key words: Personalized Learning Path, Information Systems Students, Recommender System, Collaborative Filtering, Content-Based approach

INTRODUCTION

The rapid evolution of technology and job markets in Information Technology (IT) dramatically transformed the career development landscape. Students must adhere to a continuous learning philosophy to remain competitive in the ever-changing Information ystems (IS).

Navigating the vast array of learning options in IS poses a significant challenge, as students must discern which paths will be most effective for their career advancement. Wan and Zhang[1] argued that while beneficial, the abundance of online resources can lead to confusion and decision paralysis, underscoring the need for tailored guidance. Zhou et al.[2] noted that this context necessitates a focused approach toward developing Recommender Systems (RS) for Personalized Learning Paths (PLP), catering specifically to the IS domain, as a vital tool for navigating the extensive digital learning environment. Niknam and Thulasiraman[3] stated that the emerging need for these systems is driven by the increasing obsolescence of traditional career planning and educational methods in the IS sector in the face of novel technological breakthroughs and market dynamics.

This challenge was further amplified by the necessity to align learning choices with the rapidly evolving IS industry demands. Moreover, a study by Joseph et al.[4] emphasized the critical connection between these learning opportunities and long-term career goals in IS, demanding a careful balance between immediate skill acquisition and future career objectives. Chen et al.[5] recognized the gap between the skills imparted by traditional education and those demanded in the workplace there is a pressing need for recommendation systems that align learning choices with industry

Cite this article : Phong T D T, Khang V B, Minh D N, Quynh D T, Quang D V, Thanh H T. **Personalized learning paths recommendation system with collaborative filtering and content-based approaches** . *Sci. Tech. Dev. J. - Eco. Law Manag.* 2024; ():1-10.

requirements.

This research aims to evaluate the efficacy of user-user collaborative filtering and content-based techniques in developing innovative recommender systems. With this objective, the research methodology integrates two distinct primary approaches: user-user collaborative filtering and content-based techniques to provide personalized learning pathways aligned with the Knowledge - Skill - Attitude (KSA) framework, focusing on students in the Faculty of Information Systems (FIS) at the University of Economics and Law (UEL). The objective is to develop customized systems for IS students, ensuring a seamless integration of techniques for enhanced learning experiences. This paper begins with a literature review to establish context, followed by a detailed exposition of the methodology. Subsequent sections present and discuss the research findings, exploring their implications for continuous learning in the IS domain. The paper concludes with recommendations for future research initiatives.

LITERATURE REVIEW

RS has dynamically transformed user interaction across various domains, including education, where its role in shaping PLP was increasingly recognized. To contextualize this research within this evolving landscape, Lu et al.[6] emphasized the transformative potential of RS in education, highlighting the need for high-quality, instructive reviews of current trends. These systems enhanced user experience and engagement by predicting user preferences through various algorithms.

Marappan and Saraswatikaniga[7] argued that the Collaborative Filtering (CF) approach is the most established and widely utilized method. This research underscored its fundamental reliance on the intricate dynamics of user-item interactions. This method's strength in identifying patterns among users to suggest personalized content is pivotal. CF leveraged similarities between users and items to generate personalized recommendations. Abdi et al.[8] underlined the effectiveness of Matrix Factorization in CF, particularly for large datasets, despite acknowledging the hurdles, such as data sparsity, that can affect recommendation quality. While the CF approach was celebrated for its ability to tailor recommendations based on user-item interactions, critics argued that it may need to sufficiently capture the full spectrum of user preferences, especially in diverse educational contexts. A noted by another study[9], concerns about data sparsity and privacy suggested limitations in CF's applicability without robust data handling and privacy safeguards. Furthermore, the reliance on existing user interactions could narrow learning opportunities, overlooking emerging or interdisciplinary content that could enrich the learner's experience[10].

On the other hand, Content-Based Recommender Systems (CBRS) recommend items based on a user's historical item-rating data. Murugan et al.[11] noted CBRS's prevalence in research-paper recommendations but pointed out the ambiguity in their effectiveness compared to CF. This uncertainty, often stemming from the challenges in accurately mapping user preferences to content features, was particularly relevant to this investigation. In educational settings, where the content is diverse and often complex, ensuring that recommendations are relevant and conducive to learning objectives is a significant challenge [[12], p. 72]. Lops et al.[13] also added that ensuring diversity and serendipity in recommendations remains challenging for CBRS. Another paper further contributed to this dialogue by addressing the need for diversity and serendipity in CB recommendations[7,14]. In educational RS, it is essential that the system not only caters to the known preferences of learners but also exposes them to a broader range of learning materials that could spark new interests and learning paths, a point that this research considers.

Discussing previous work on RS in PLP, Kirkwood and Price[15] discussed previous work on RS in PLP and indicated a gap between theory and practice in the field of Technology-Enhanced Learning (TEL). This underdevelopment in RS for PLP has been an area our research directly addresses. The author also stressed the need for more research on RS assessment, pointing out the potential discrepancies between these systems' perceived and actual effectiveness[13]. This is considered a deeper evaluation of RS, an aspect that is central to this study.

Implementing RS in PLP within educational settings, notably higher education, presents a unique set of challenges and opportunities. A study[16] showed that balancing customized learning experiences with curriculum frameworks and job requirements remains challenging. Huu et al.[17] stated that while RS can build highly personalized learning paths, aligning these with expected learning outcomes and job descriptions was a tension this paper seeks to explore. Their observation revealed a discrepancy between theoretical advancements and practical applications in this field. The scarcity of RS in PLP highlights a significant gap where potential benefits are yet to be fully harnessed in real-world educational settings[18].

In conclusion, the potential of RS in education to enhance PLP ha been clarified, yet various challenges need to be addressed. As a result, this creates a need for the adoption of data-driven research to assess the effectiveness of RS in educational contexts. This approach is also vital for substantiating the potential of RS in improving educational outcomes [19]. Future research would focus on developing RS that are not only technologically advanced but also pedagogically sound, effectively bridging the gap between user needs and the evolving requirements of the modern workforce.

METHODOLOGY

The current study aims to assess the performance of personalized RS by conducting a comparative analysis of two distinct models, including the CF and CB. Figure 1 outlines five specific steps of the research framework for this project, beginning with the data-storing phase to model evaluation in a structured workflow.

Dataset Description

Figure 2 can be considered a comprehensive compilation of data that provides insights into the competency needs of various IT job titles. It includes 7,000 entries and 13 columns outlining essential IT skills and competencies required for each unique job title. Each skill was quantified using advanced Natural Language Processing (NLP) techniques to rank each skill based on market relevance and demand to ensure a comprehensive resource for understanding IT skill requirements. The research also utilized Bloom's Taxonomy to ensure a focused, all-inclusive approach to ascertain the proposed IT skill requirements.

The Knowledge Dataset includes 77 courses covering fundamental programming principles in specialized fields such as machine learning and cybersecurity. The corresponding *'learning_outcomes'* column highlights the practicality and significance of the course material in addressing real-world challenges and job responsibilities to establish a clear correlation between academic pursuits and the professional skill sets essential to excel in the IS field.

The Attitude dataset was established to highlight vital personal qualities. The dataset includes *'job_title'* and '*attitude*' columns that link attributes like problem-solving, adaptability, teamwork, and analytical thinking to specific IT roles. The '*attitude*' columns are derived from an analysis that emphasizing the top three qualities of each job title. This underscores the importance of continuous learning and collaboration in navigating the evolving technological landscape and executing complex projects.

Algorithm Implementation

User-User-Based Collaborative Filtering

This RS utilizes User-Based CF to produce personalized recommendations by analyzing mutual preferences and user interactions. Heap et al. [20] said that this approach adopts the Cosine imilarity - a widely recognized metric calculating the cosine of the angle between two non-zero vectors in a multi-dimensional space, to determine the similarity between user and job profiles. The formula is described as follows:

$$Cosine\ Similarity = \frac{\underline{A}\underline{B}}{||\underline{A}||.||\underline{B}||} \qquad (1)$$

Here, A and B are user interaction vectors. For example, if User X and Job Y have interacted with skills represented by vectors [3, 2, 0, 5] and [1, 0, 4, 4], respectively, the cosine similarity was calculated based on these vectors, providing a quantifiable measure of their preference alignment. Initially, a skill-rating matrix was established, capturing the interactions and preferences of all users within the system. Subsequently, similarity scores were computed for each user pair using the cosine similarity measure. Recommendations were then generated based on an aggregating preferences from from users deemed similar. This aggregation was weighted by their respective similarity scores, ensuring that more similar users had a greater influence on the recommendations.

Content-based approach

Within CB method, Lu [21] said that the KMeans clustering algorithm is predominantly employed to segment job roles into discrete clusters based on shared characteristics, such as skills and qualifications. The current study utilized multiple criteria for clustering, including skill relevance and job title similarities, resulting in informative and valuable clusters that accurately mirror the real-world grouping of job roles (Figure 3).

CB is a commonly employed technique that enables personalized recommendations to users. This technique involves the computation of similarity between an item and a user based on the item's features (1). Suriati et al. [22] stated an item matrix A with element $a_{i,j,}$ showing the relationship between item i and feature j. Further, a rating matrix R with element $r_{u,i}$ is also required, denoting the rating assigned by user u to item i. Suriati et al. [22] stated that the fundamental objective behind this approach is to construct a user profile matrix B with element $b_{i,j}$ signifying the relationship between user u and feature j. This can be accomplished by multiplying the rating matrix and the item matrix, as demonstrated in equation (2).

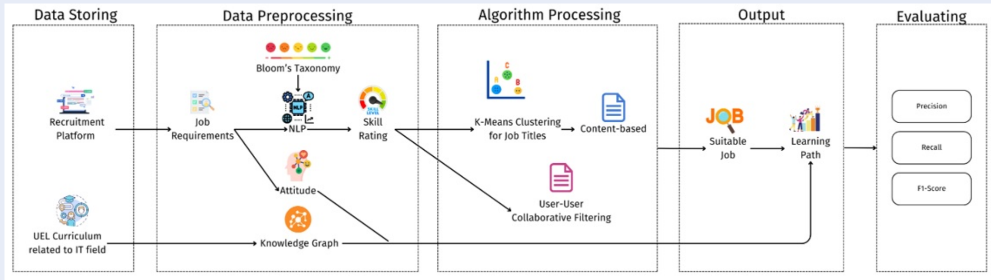

Figure 1: Research Framework (Source: Authors)

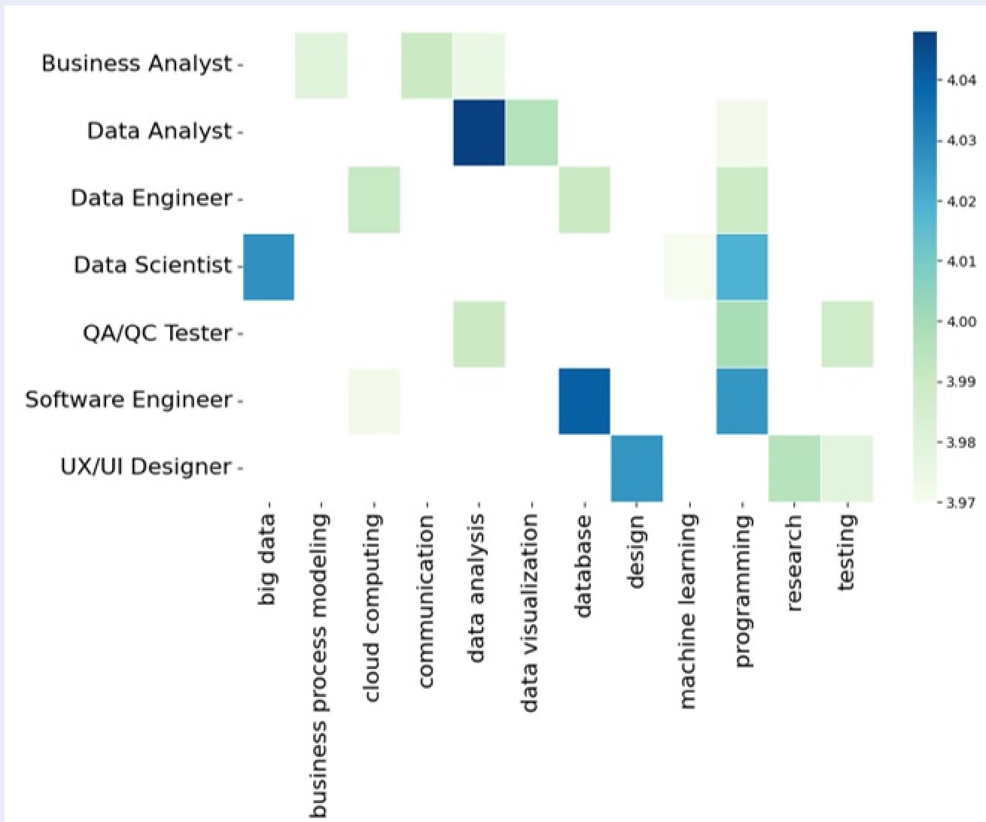

Figure 2: Skill Dataset (Source: Authors)

B = R × A (2)

The two types of vectors, including item profile a_i and user profile b_u are, used as indices to construct the cosine similarity, indicating the user's and item's similarity level. The score range, between -1 and 1, reflects the proximity the proximity between the vectors, with a score close to 1 indicating a high likelihood of match. Equation (3) is used to predict user ratings for items, with x representing the highest achievable rating within the system. This equation is based on the similarity score between the user and item vectors and allows us to predict users' preferences and provide recommendations accordingly.

$$P_{u,i} = (x - t)\, sim\, (b_u, a_i) + t \quad (3)$$

Model Evaluation Metrics

To assess this RS's performance, a suite of evaluation metrics including recision, Recall and F1- core were employed. These metrics provide a comprehensive

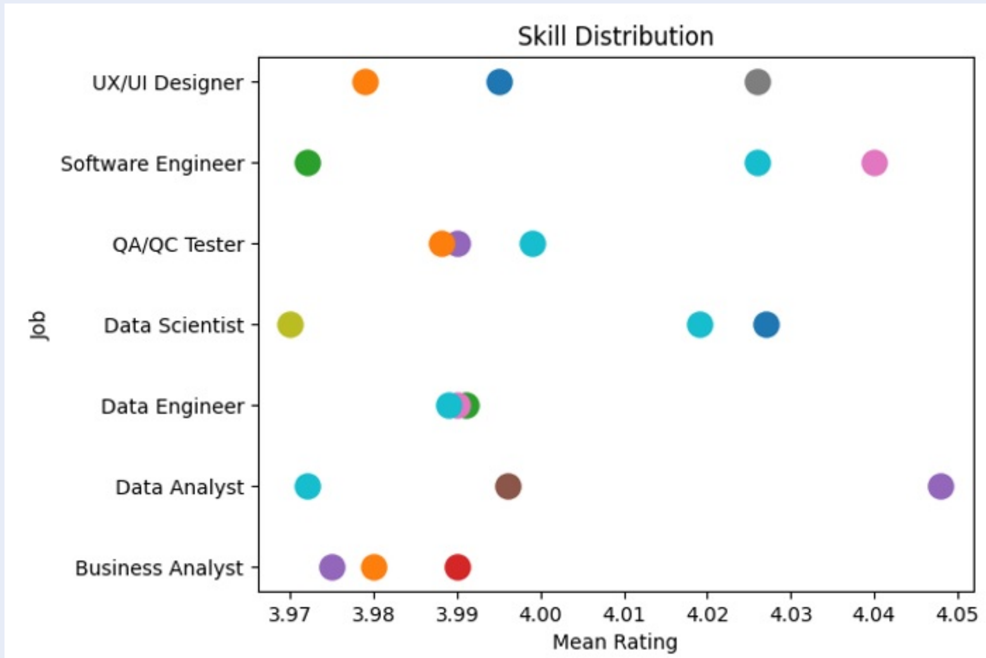

Figure 3: Job Positions Clustering (Source: Authors)

understanding of the system's accuracy and effectiveness.

Precision

Sun et al.[23] defined recision in the context of this RS as the ratio of the True Positives (i.e., correctly recommended items) to the total number of items that the system classified as positive, which encompassed both True Positives (TP) and False Positives (FP). Mathematically, Precision was expressed as:

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

Where TP denoted True Positives and FP denoted FP. A higher Precision score indicated of the system's effectiveness in ensuring that the recommended learning paths were relevant to the user's needs and preferences.

Recall

On the other hand, Solanki et al.[24] stated that recall measured the system's capability to identify all relevant items. It was calculated as the ratio of the TP to the sum of TP and False Negatives (FN), represented by:

$$Recall = \frac{TP}{(TP+FN)} \tag{5}$$

In this scenario, a high Recall score implied that the system was adept at capturing a comprehensive range of suitable job positions and courses for the user.

F1 score

Chen et al.[25] noted that F1-Score provide a balanced system performance view by harmonizing Precision and Recall. This metric was the harmonic mean of Precision and Recall and was formulated as:

$$F1-Score = 2 \times \frac{Precision \ x \ Recall}{Precision + Recall} \tag{6}$$

The F1-Score was a pivotal metric, especially in scenarios where there was an imbalance in the dataset or unequal distribution of classes, as it ensures that the recommendations' relevance and completeness are accounted for.

While it is essential to recognize the limitations of User-Based CF, which relies on existing employee interactions, this approach is highly effective at capturing and analyzing user preference patterns[24,26]. On the other hand, the CB approach has been criticized for its narrow focus on specific characteristics of items, such as courses or job roles, that employees have previously interacted with or shown interest in. However, this approach is instrumental in aligning recommendations with specific content attributes. By evaluating these two methods, the research identifies the inherent potential of each model to contribute uniquely to the development of RS in the context of employment and educational alignment. Incorporating both approaches allows for a more robust recommendation system capable of addressing a diverse range of user needs and scenarios[27,28]. For instance, a hybrid model can mitigate the cold start problem associated with CF by utilizing CB recommendations for new users or items until sufficient interaction data becomes available. Conversely, the potential over-specialization of CB can be balanced by CF's ability to introduce diversity and serendipity into the recommendation mix.

EXPERIMENTAL RESULT AND DISCUSSION

Experimental R esult

The empirical evaluation of this paper encompassed two distinct models: CF and CB. The performance of each model was rigorously assessed across three key metrics: Precision, Recall, and F1-Score. The results presented herein offer a clear, objective view of the models' effectiveness without delving into speculative interpretations.

Discussion

Results Analysis

Collaborative Filtering Model

The first model under scrutiny was the CF approach. The recision metric for this model was recorded at a perfect score of 1.00 (Table 1), signifying an exemplary level of accuracy where every recommended item (i.e., learning paths) was deemed relevant. This high recision indicates the model's robustness in filtering out non-relevant recommendations, ensuring that learners are only presented with the most pertinent learning paths.

However, the Recall score was slightly lower at 0.83 (Table 1), implying that while the model was highly accurate in its recommendations, it did not capture the entire spectrum of relevant items. Such a scenario might lead to missing out on pertinent learning paths that could be beneficial for the learner.

The F1-Score, which is the harmonic mean of recision and Recall, stood at 0.91 (Table 1). This score is significant as it demonstrates a balanced trade-off between recision and Recall, underscoring the overall effectiveness of the CF model in providing relevant and comprehensive learning path recommendations.

Content-Based Model

The second model, the CB approach, demonstrated a slightly lower recision score of 0.90. This indicates a minor reduction in accuracy compared to the CF model. While most recommendations were relevant, only a small fraction may have been partially pertinent to the learners' needs.

In terms of Recall, the CB model scored 0.86 (Table 1), marginally outperforming the CF model. This higher Recall suggests that the CB model was more effective in identifying a broader range of relevant learning paths, albeit with a slight compromise in recision.

The F1-Score for the CB model was calculated at 0.84 (Table 1). Although slightly lower than the CF model, this score still reflects a robust performance, indicating that the CB model is a viable alternative, particularly in scenarios where a broader identification of relevant items is prioritized over precision.

Implications

For University

Duan et al.[29] identified the integration of recommendation systems within higher education frameworks as a pivotal strategy for enhancing curriculum relevance and ensuring alignment with labor market demands. Management factors such as strategic planning, stakeholder engagement, and continuous curriculum assessment play critical roles in this integration process[28,29]. Strategic planning involves the adoption of forward-looking models that facilitate early identification of students' career goals and academic interests, allowing universities, specifically in the context of this study, the UEL, to tailor their programs to better meet both student aspirations and the evolving needs of the industry. Forsythe[30] provided the insight that stakeholder engagement, involving collaboration with industry partners, educators, and students, is essential for effectively understanding and responding to market trends and educational expectations.

Furthermore, continuous curriculum assessment ensures that academic offerings remain dynamic and responsive to changes in the labor market, thereby maintaining the applicability and value of the skills and knowledge taught[30,31]. The adoption of such systems necessitates universities to remain vigilant and responsive to current industry trends to preserve the relevance of their courses. The significance of leveraging technology in education, as highlighted by Smith and Worsfold[31], is supported by empirical evidence. Studies have shown that TEL can improve student engagement, higher retention rates, and better learning outcomes[10]. Furthermore, Alamri et al. [[32], p.339] stated that PLP has been increased student satisfaction and academic achievement.

FIS can also utilize data analytics to monitor and analyze trends within both student performance and industry requirements. This approach supports the adjustment of courses that are theoretically sound and

Table 1: Model Evaluation Metrics (Source: Authors)

	Collaborative Filtering	Content- ased Approach
Precision	1.00	0.90
Recall	0.83	0.86
F1-Score	0.91	0.84

practically relevant. Alamri et al. [32, p.331] discussed the potential of learning technology models to support personalization within blended learning environments in higher education. Studies by Cubit[33] confirmed that personalized learning environments increase student engagement and achievement, illustrating the positive impact of technology-enabled personalization. Similarly, research by Vallée et al.[34] suggested that students in online and blended learning settings often achieve better outcomes compared to traditional classroom settings, thanks to the adaptability offered by TEL. Further supporting this, Freitas et al.[35] also found that personalized e-learning systems contribute to higher retention rates in higher education by addressing individual learning preferences and sustaining student interest.

Moreover, implementing RS should be considered part of a broader institutional change towards a more learner-centered approach. This shift requires a re-evaluation of teaching methodologies, assessment practices, and the overall student experience. The challenges and solutions associated with AI-based personalized e-learning systems are outlined in a study that point to the necessity of aligning educational technologies with pedagogical strategies and learning outcomes[36].

For Students

Xiao et al.[37] argued that students stand to benefit immensely from personalized educational experiences facilitated by RS. Such systems enable students to make informed decisions regarding their educational and career trajectories, enhancing their ability to align their training programs and course selections with their long-term professional goals. This personalized approach not only aids in students' professional and personal development but also fosters a more engaging and relevant learning experience. As illustrated by Alamri et al. [32, p.345], the ability to tailor one's academic path directly contributes to improved learning outcomes and better preparation for the job market. Longitudinal studies, such as those by the Bill & Melinda Gates Foundation, reinforced the value of personalized learning, indicating improved standardized test scores among students and increased confidence in their college and career prospects. This confidence, rooted in personalized educational experiences, paves the way for long-term success in both educational and professional arenas.

Furthermore, early exposure to career exploration platforms can significantly impact high school students, enabling them to make more informed decisions about their future education and employment opportunities. For instance, platforms like Naviance or Career Cruising offer personalized assessments that match students' interests and strengths with potential careers, guiding them toward relevant educational programs[38]. By engaging with these platforms, students can explore various career options, understand the educational requirements for each role, and plan their high school courses accordingly. This informed decision-making process ensures that students are better prepared for post-secondary education and the workforce with confidence and clarity, aligning their academic pursuits with their career aspirations and the current job market demands[39].

For Businesses

From an employment perspective, RS would revolutionize the recruitment process by facilitating the identification of graduates whose education and skill sets align with specific job requirements. This alignment not only enhances the efficiency of the recruitment process but also optimizes resource utilization. Companies benefit from a streamlined recruitment process that is more closely aligned with industry trends, ultimately improving the quality and speed of the hiring process. The integration of such systems signifies a shift towards more data-driven and customized educational experiences, underscoring the mutual benefits of aligning educational programs with real-world applications and market needs. However, it is imperative to critically examine their role in perpetuating or mitigating biases during the hiring process. Studies such as those by Gianfrancesco et al.[40] revealed the inherent risk of these systems reinforcing existing societal and organizational biases, particularly when algorithms are trained on historical data that may reflect prejudiced hiring practices. This requires the need for deploying bias correction mechanisms and ensuring that recommendation systems are regularly audited for fairness.

This research makes significant theoretical and practical contributions to personalized learning and RS in IS. The study advances the understanding of how CF and CB approach can be tailored and integrated within the context of PLP. It also provides actionable insights for educators and developers on implementing these RSs to enhance educational content and career development tools. The research has the potential to pave the way for future studies on hybrid recommendation methodology, which suggest a new direction for combining different approaches to improve the personalization and effectiveness of learning paths in I and other fields.

CONCLUSION AND FUTURE WORK

Conclusion

This project evaluated the accuracy and performance of the learning path RS using User-based CF and CB techniques separately. The research's findings confirm the initial hypothesis that CF and CB models would each exhibit distinct strengths in PLP. The former model achieved an absolute recision rate of 100%, while the latter excelled in Recall, identifying 85% of relevant learning paths. These insights extend beyond I , suggesting potential applications in diverse educational fields, from digital marketing to healthcare training. The capability of CF and CB model to adapt to changing user preferences and the dynamic nature of I sector content underscores their profound utility in real-world applications, ensuring that learning recommendations remain relevant and personalized, crucial for IS students seeking to stay abreast of technological advancements and emerging trends.

Limitations

When used independently, the performance of the proposed models has some specific limitations indicated by the application. For CF, essential barriers like data sparsity may reduce its ability to suggest new or uncommon learning paths. This obstacle arises because CF relies heavily on existing user interactions, making it difficult to suggest items with few or no ratings[41]. Conversely, the CB model, while effective in matching specific content attributes, may overlook the broader preferences and behavioral patterns of users, potentially limiting its ability to meet the diverse needs of learners in the IS.

Future Development

Future efforts will focus on developing a hybrid model, combining the behavioral analysis strength of CF with the precise content matching of the CB technique. This hybrid approach aims to mitigate the drawbacks of both models by integrating their strengths and proposing a more accurate and comprehensive PLP RS[42]. This approach directly addresses the research objective of evaluating the efficacy of different RS models in enhancing personalized educational experiences, aligning more closely with the progressed needs of IT education and career development. In addition, the current evaluation metrics, namely Precision, Recall, and F1-Score, focus primarily on the relevance and utility of the recommendation models. Moving forward, to better evaluate the hybrid model and provide a more nuanced understanding of its efficacy, it is crucial to incorporate metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Normalized Discounted Cumulative Gain (NDCG). This metrics expansion will supplement the current evaluation framework, providing a deeper understanding of this research's findings and the practical application of RS in education settings.

ACKNOWLEDGE MENTS

This research is funded by University of Economics and Law, Vietnam National University Ho Chi Minh City / VNU-HCM

LIST OF ABBREVIATIONS

RS: Recommender System
IS: Information Systems
CF: Collaborative Filtering
CB: Content-Based
FIS: Faculty of Information Systems
UEL: University of Economics and Law
CBRS: Content-Based Recommender Systems
TEL: Technology-Enhanced Learning
PLP: Personalized Learning Path
IT: Information Technology
KSA: Knowledge - Skill - Attitude
NLP: Natural Language Processing
TP: True Positive
FP: False Positive
FN: False Negative

COMPETING INTERESTS

The author declares that there are no conflicts of interest in the publication of this article.

AUTHORS' CONTRIBUTION

Tran Duong Thanh Phong and Ho Trung Thanh: Conceptualized and designed the study, Wrote the original manuscript, and Reviewed and Edited the article.

Vu Bao Khang and Ho Trung Thanh: Conducted the data preparation, Developed and implemented the algorithm, Conducted data analysis, Wrote the Experimental results.

Doan Nhat Minh: Conducted the data preparation, performed the analytical calculations, and Wrote the Discussion & Conclusion.

Dang Truc Quynh and Ho Trung Thanh: Conducted the Literature Review & Introduction, Contributed to the visualization of the study, and Reviewed the article.

Dang Viet Quang and Ho Trung Thanh: Assisted with the data preparation, Contributed to the experimental design, Wrote the Methodology, and Reviewed the article.

REFERENCES

1. Wan L, Zhang L. Personalized Learning Path Generation based on Network Embedding and Learning Effects. 2019 IEEE 10th International Conference on Software Engineering and Service Science (ICSESS) [Internet]. 2019 Oct 1;Available from: https://doi.org/10.1109/icsess47205.2019.9040721.
2. Zhou Y, Huang C, Hu Q, Zhu J, Tang Y. Personalized learning full-path recommendation model based on LSTM neural networks. Information Sciences [Internet]. 2018 May 1;444:135-52;Available from: https://doi.org/10.1016/j.ins.2018.02.053.
3. Niknam M, Thulasiraman P. LPR: A bio-inspired intelligent learning path recommendation system based on meaningful learning theory. Education and Information Technologies [Internet]. 2020 Feb 27;25(5):3797-819;Available from: https://doi.org/10.1007/s10639-020-10133-3.
4. Joseph L, Abraham S, Mani BP, Rajesh N. Exploring the Effectiveness of Learning Path Recommendation based on Felder-Silverman Learning Style Model: A Learning Analytics Intervention Approach. Journal of Educational Computing Research [Internet]. 2022 Feb 10;60(6):1464-89;Available from: https://doi.org/10.1177/07356331211057816.
5. Chen Y, Huang NF, Tzeng JW, Lee CA, Huang YX, Huang HH. A Personalized Learning Path Recommender System with LINE Bot in MOOCs Based on LSTM. 2022 11th International Conference on Educational and Information Technology (ICEIT) [Internet]. 2022 Jan 6;Available from: https://doi.org/10.1109/iceit54416.2022.9690754.
6. Lu J, Wu D, Mao M, Wang W, Zhang G. Recommender system application developments: A survey. Decision Support Systems [Internet]. 2015 Jun 1;74:12-32;Available from: https://doi.org/10.1016/j.dss.2015.03.008.
7. Marappan R, Saraswatikaniga R. Recent Recommender Systems and Analysis of the Machine Learning Public Instances. 2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT) [Internet]. 2023 Sep 8;Available from: https://doi.org/10.1109/cisct57197.2023.10351295.
8. Abdi MH, Okeyo G, Mwangi RW. Matrix Factorization Techniques for Context-Aware Collaborative Filtering Recommender Systems: A survey. Computer and Information Science [Internet]. 2018 Mar 16;11(2):1;Available from: https://doi.org/10.5539/cis.v11n2p1.
9. Raj S, Sahoo AK, Pradhan C. Privacy preserving in Collaborative Filtering Based Recommender System: A Systematic Literature review. In: Advances in intelligent systems and computing [Internet]. 2020. p. 513-22;Available from: https://doi.org/10.1007/978-981-15-2414-1_52.
10. Beel J, Gipp B, Langer S, Breitinger C. Research-paper recommender systems: a literature survey. International Journal on Digital Libraries [Internet]. 2015 Jul 26;17(4):305-38;Available from: https://doi.org/10.1007/s00799-015-0156-0.
11. Murugan M, Vijayan R, Saravanan A, Jaisankar S. Performance enhancement of centrally finned twist inserted solar collector using corrugated booster reflectors. Energy [Internet]. 2019 Feb 1;168:858-69;Available from: https://doi.org/10.1016/j.energy.2018.11.134.
12. Alamri H, Watson SL, Watson WR. Learning Technology Models that Support Personalization within Blended Learning Environments in Higher Education. TechTrends [Internet]. 2020 Jul 31;65(1):62-78;Available from: https://doi.org/10.1007/s11528-020-00530-3.
13. Lops P, De Gemmis M, Semeraro G. Content-based recommender Systems: state of the art and trends. In: Springer eBooks [Internet]. 2010. p. 73-105;Available from: https://doi.org/10.1007/978-0-387-85820-3_3.
14. Koohi H, Kiani K. User based Collaborative Filtering using fuzzy C-means. Measurement [Internet]. 2016 Sep 1;91:134-9;Available from: https://doi.org/10.1016/j.measurement.2016.05.058.
15. Kirkwood A, Price L. Technology-enhanced learning and teaching in higher education: what is 'enhanced' and how do we know? A critical literature review. Learning, Media and Technology [Internet]. 2013 Feb 20;39(1):6-36;Available from: https://doi.org/10.1080/17439884.2013.770404.
16. Medina AER, Martinell AR. Recommender System in Higher Education: A Preliminary Study of State of the art. 2019 XIV Latin American Conference on Learning Technologies (LACLO) [Internet]. 2019 Oct 1;Available from: https://doi.org/10.1109/laclo49268.2019.00047.
17. Huu PN, Tangworakitthaworn P, Gilbert L. Towards Self-Regulated Individual Learning Path Generation Using Outcome Taxonomies and Constructive Alignment. 2021 IEEE International Conference on Engineering, Technology & Education (TALE) [Internet]. 2021 Dec 5;Available from: https://doi.org/10.1109/tale52509.2021.9678777.
18. Black C, Freeman C, Rawlings A. Problem-based learning: design development of female chef's jackets. International Journal of Fashion Design, Technology and Education [Internet]. 2017 Jul 4;11(1):123-8;Available from: https://doi.org/10.1080/17543266.2017.1332245.
19. Batmaz Z, Yürekli A, Bilge A, Kaleli C. A review on deep learning for recommender systems: challenges and remedies. Artificial Intelligence Review [Internet]. 2018 Aug 29;52(1):1-37;Available from: https://doi.org/10.1007/s10462-018-9654-y.
20. Heap B, Krzywicki A, Wobcke W, Bain M, Compton P. Combining career progression and profile matching in a job recommender system. In: Lecture Notes in Computer Science [Internet]. 2014. p. 396-408;Available from: https://doi.org/10.1007/978-3-319-13560-1_32.
21. Lu Z. A hybrid movie recommendation algorithm based on optimized K-Means clustering. 2022 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC) [Internet]. 2022 Apr 14;Available from: https://doi.org/10.1109/ipec54454.2022.9777625.
22. Suriati S, Dwiastuti M, Tulus T. Weighted hybrid technique for recommender system. Journal of Physics: Conference Series [Internet]. 2017 Dec 1;930:012050;Available from: https://doi.org/10.1088/1742-6596/930/1/012050.
23. Sun C, Gao R, Xi H. Big data based retail recommender system of non E-commerce. Fifth International Conference on Computing, Communications and Networking Technologies (ICCCNT) [Internet]. 2014 Jul 1;Available from: https://doi.org/10.1109/icccnt.2014.6963129.
24. Solanki S, Verma S, Chahar K. A comparative study of information retrieval using machine learning. In: Algorithms for intelligent systems [Internet]. 2020. p. 35-42;Available from: https://doi.org/10.1007/978-981-15-0222-4_3.
25. Chen P, Lu Y, Zheng VW, Chen X, Yang B. KnowEDU: A system to Construct Knowledge Graph for Education. IEEE Ac-

cess [Internet]. 2018 Jan 1;6:31553-63;Available from: https://doi.org/10.1109/access.2018.2839607.

26. Jiang S, Qian X, Shen J, Fu Y, Mei T. Author Topic Model based Collaborative Filtering for Personalized POI Recommendation. IEEE Transactions on Multimedia [Internet]. 2015 Jan 1;1;Available from: https://doi.org/10.1109/tmm.2015.2417506.

27. Fernández-Tobías I, Braunhofer M, Elahi M, Ricci F, Cantador I. Alleviating the new user problem in collaborative filtering by exploiting personality information. User Modeling and User-Adapted Interaction [Internet]. 2016 Feb 6;26(2-3):221-55;Available from: https://doi.org/10.1007/s11257-016-9172-z.

28. Aslanian E, Radmanesh M, Jalili M. Hybrid Recommender Systems based on Content Feature Relationship. IEEE Transactions on Industrial Informatics [Internet]. 2016 Jan 1;1;Available from: https://doi.org/10.1109/tii.2016.2631138.

29. Duan L, Street WN, Xu E. Healthcare information systems: data mining methods in the creation of a clinical recommender system. Enterprise Information Systems [Internet]. 2011 May 1;5(2):169-81;Available from: https://doi.org/10.1080/17517575.2010.541287.

30. Forsythe LP, Ellis LE, Edmundson L, Sabharwal R, Rein A, Konopka K, et al. Patient and stakeholder engagement in the PCORI pilot Projects: description and lessons learned. Journal of General Internal Medicine [Internet]. 2015 Jul 10;31(1):13-21;Available from: https://doi.org/10.1007/s11606-015-3450-z.

31. Smith C, Worsfold KA. Unpacking the learning-work nexus: 'priming' as lever for high-quality learning outcomes in work-integrated learning curricula. Studies in Higher Education [Internet]. 2013 Jul 22;40(1):22-42;Available from: https://doi.org/10.1080/03075079.2013.806456.

32. Alamri H, Lowell VL, Watson WR, Watson SL. Using personalized learning as an instructional approach to motivate learners in online higher education: Learner self-determination and intrinsic motivation. Journal of Research on Technology in Education [Internet]. 2020 Jun 22;52(3):322-52;Available from: https://doi.org/10.1080/15391523.2020.1728449.

33. Cayubit RFO. Why learning environment matters? An analysis on how the learning environment influences the academic motivation, learning strategies and engagement of college students. Learning Environments Research [Internet]. 2021 Aug 9;25(2):581-99;Available from: https://doi.org/10.1007/s10984-021-09382-x.

34. Vallée A, Blacher J, Cariou A, Sorbets E. Blended Learning Compared to Traditional Learning in Medical Education: Systematic Review and Meta-Analysis. Journal of Medical Internet Research [Internet]. 2020 Aug 10;22(8):e16504;Available from: https://doi.org/10.2196/16504.

35. De Freitas S, Gibson D, Du Plessis C, Halloran P, Williams EA, Ambrose M, et al. Foundations of dynamic learning analytics: Using university student data to increase retention. British Journal of Educational Technology [Internet]. 2014 Oct 15;46(6):1175-88;Available from: https://doi.org/10.1111/bjet.12212.

36. Khanal SS, Prasad PWC, Alsadoon A, Maag A. A systematic review: machine learning based recommendation systems for e-learning. Education and Information Technologies [Internet]. 2019 Dec 14;25(4):2635-64;Available from: https://doi.org/10.1007/s10639-019-10063-9.

37. Xiao J, Wang M, Jiang B, Li J. A personalized recommendation system with combinational algorithm for online learning. Journal of Ambient Intelligence and Humanized Computing [Internet]. 2017 Mar 4;9(3):667-77;Available from: https://doi.org/10.1007/s12652-017-0466-8.

38. Morningstar ME, Lombardi A, Fowler C, Test DW. A College and career readiness framework for secondary students with disabilities. Career Development and Transition for Exceptional Individuals [Internet]. 2015 Jun 15;40(2):79-91;Available from: https://doi.org/10.1177/2165143415589926.

39. Shahriar S, Ramesh J, Towheed M, Ameen T, Sagahyroon A, Al-Ali AR. Narrative Integrated Career Exploration Platform. Frontiers in Education [Internet]. 2022 Mar 10;7;Available from: https://doi.org/10.3389/feduc.2022.798950.

40. Gianfrancesco M, Tamang S, Yazdany J, Schmajuk G. Potential biases in machine learning algorithms using electronic health record data. JAMA Internal Medicine [Internet]. 2018 Nov 1;178(11):1544;Available from: https://doi.org/10.1001/jamainternmed.2018.3763.

41. Chen R, Hua Q, Chang Y, Wang B, Zhang L, Kong X. A survey of collaborative Filtering-Based Recommender systems: from traditional methods to hybrid methods based on social networks. IEEE Access [Internet]. 2018 Jan 1;6:64301-20;Available from: https://doi.org/10.1109/access.2018.2877208.

42. Afoudi Y, Lazaar M, Achhab MA. Hybrid recommendation system combined content-based filtering and collaborative prediction using artificial neural network. Simulation Modelling Practice and Theory [Internet]. 2021 Dec 1;113:102375;Available from: https://doi.org/10.1016/j.simpat.2021.102375.

Tạp chí Phát triển Khoa học và Công nghệ – Economics-Law and Management 2024, ():1-1

Open Access Full Text Article

Bài nghiên cứu

Hệ thống khuyến nghị lộ trình học cá nhân hóa với các phương pháp lọc cộng tác và dựa trên nội dung

Trần Dương Thanh Phong[1,2], Vũ Bảo Khang[1,2], Đoàn Nhật Minh[1,2], Đặng Trúc Quỳnh[1,2], Đặng Việt Quang[1,2], Hồ Trung Thành[1,2,*]

TÓM TẮT

Các hệ thống khuyến nghị đã trải qua một sự phát triển vượt trội, giúp tái định hình tương tác của người dùng trên nhiều lĩnh vực khác nhau. Đặc biệt, việc chú trọng phát triển các lộ trình học tập cá nhân hóa đã tăng lên đáng kể trong lĩnh vực giáo dục. Bài nghiên cứu này đi sâu vào đánh giá hiệu suất của các kỹ thuật khuyến nghị dựa trên nội dung và lọc cộng tác dựa trên người dùng, nhằm phát triển hệ thống khuyến nghị sáng tạo và được thiết kế riêng cho sinh viên. Bằng cách tích hợp bộ dữ liệu chính dựa trên mô hình Kiến thức - Kỹ năng - Thái độ cho sinh viên tại Trường Đại học Kinh tế - Luật, nghiên cứu này đánh giá mức độ hiệu quả của hai mô hình riêng biệt trong việc phát triển các hệ thống khuyến nghị cá nhân hóa. Hơn nữa, việc đánh giá thực nghiệm của hai mô hình này, gồm phương pháp lọc cộng tác và kỹ thuật dựa trên nội dung, qua các chỉ số như độ chính xác, độ phủ và điểm F1, cung cấp cái nhìn toàn diện về hiệu quả của chúng trong việc xây dựng hệ thống khuyến nghị cho trường Đại học Kinh tế - Luật. Kết quả cho thấy phương pháp lọc cộng tác đạt điểm tuyệt đối về độ chính xác. Trong khi đó, kỹ thuật dựa trên nội dung thể hiện chỉ số độ phủ vượt trội, cho thấy tiềm năng của nó trong việc đáp ứng đa dạng các nhu cầu trong giáo dục. Bài nghiên cứu này cũng nhấn mạnh vai trò chuyển đổi của các hệ thống khuyến nghị trong giáo dục của bậc đại học, đặc biệt là trong việc nâng cao sự tham gia của sinh viên thông qua trải nghiệm học tập cá nhân hóa và điều chỉnh chương trình học phù hợp với yêu cầu của các ngành công nghiệp. Nhận thức được những hạn chế khi triển khai từng mô hình riêng lẻ, trong tương lai, nghiên cứu đề xuất một phương pháp lai kết hợp những ưu điểm của cả phương pháp lọc cộng tác và kỹ thuật dựa trên nội dung, nhằm giảm thiểu những nhược điểm hiện tại của từng mô hình. Những kết quả này cung cấp thông tin hữu ích cho sinh viên, các trường đại học và doanh nghiệp để cải thiện nội dung giáo dục và các công cụ phát triển nghề nghiệp, đồng thời mở đường cho các nghiên cứu trong tương lai về các phương pháp khuyến nghị lai, hứa hẹn mang lại trải nghiệm học tập phù hợp và hiệu quả hơn cho người học.

Từ khoá: Lộ trình học tập cá nhân hóa, sinh viên Hệ thống Thông tin, Hệ khuyến nghị, Lọc cộng tác, Lọc dựa trên nội dung

[1]*Trường đại học Kinh tế - Luật, thành phố Hồ Chí Minh, Việt Nam*

[2]*Đại học Quốc gia Việt Nam, thành phố Hồ Chí Minh, Việt Nam*

Liên hệ

Hồ Trung Thành, Trường đại học Kinh tế - Luật, thành phố Hồ Chí Minh, Việt Nam

Đại học Quốc gia Việt Nam, thành phố Hồ Chí Minh, Việt Nam

Email: thanhht@uel.edu.vn

Lịch sử

- Ngày nhận: 19-02-2024
- Ngày chấp nhận: 27-5-2024
- Ngày đăng:

DOI :

Trích dẫn bài báo này: Phong T D T, Khang V B, Minh D N, Quỳnh D T, Quang D V, Thành H T. **Hệ thống khuyến nghị lộ trình học cá nhân hóa với các phương pháp lọc cộng tác và dựa trên nội dung**. *Sci. Tech. Dev. J. - Eco. Law Manag.* 2024; ():1-1.